Demand Pattern Classification & Forecasting

Forecasting is the process of predicting, in terms of quantities, the requirements of inventory items. This acts as the backbone of the demand planning process and has wide implications on daily operational decision-making. Forecasting process is typically done at the lowest physical inventory location level within the organizational hierarchy; branches and distribution centers, for example. However, it often yields valuable insights when performed at higher aggregate levels

Figure 1: Forecasting Framework

Demand Pattern Analysis

Demand pattern classification is a critical step to help identify nature of demand so that an appropriate forecast model can be selected for the forecast process. Most companies do not have a demand classification process.

Some of the Demand Characteristics are as follows:

- Random (unpredictable)
- Trend
- Seasonal
- Intermittency (Slow-move) ←→ Regular / Irregular
- Lumpiness (Peaks & Valleys) ←→ Erratic / Non-erratic

Forecasting Model Framework

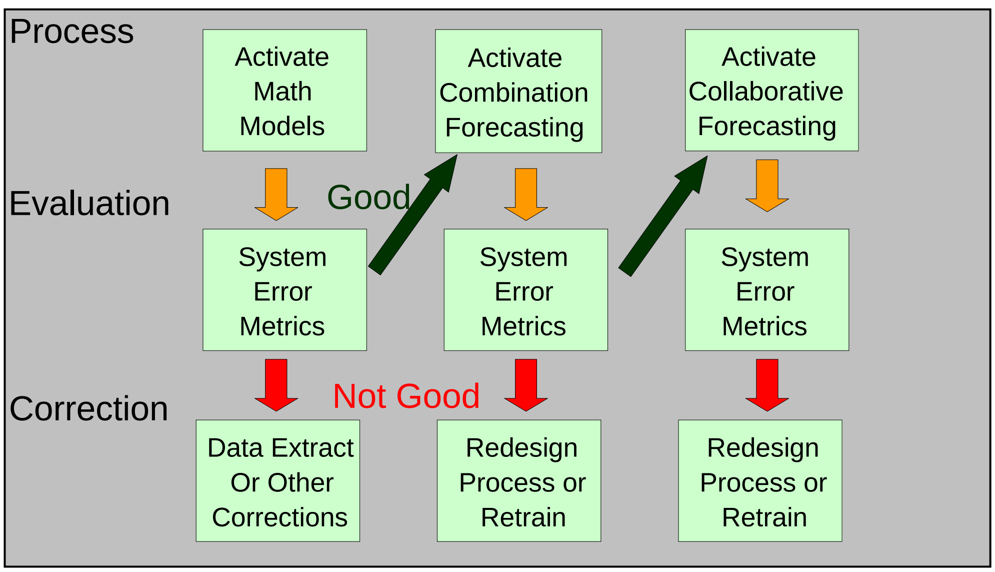
Several theoretical forecasting models that have been developed over the course of the past few decades can be broadly categorized into: 1) judgmental, 2) quantitative, and 3) combination of both. Judgmental techniques like Delphi method are useful when situations call for the expert opinion of a planner who analyzes both internal and external factors, for example, in the case of a newly introduced product with no historical data and no similarity to any other product.

Statistical Models: When demand history is available, quantitative models can be employed to use the history to make future projections. There are several mathematically complex models available depending on the nature of data, the broadly known ones being the moving average, exponential smoothing, and regression. Specialized models developed for slow-moving items include the *Croston* model, and probabilistic forecasting models such as bootstrapping and simulation.

Combination Forecasting: This involves using a proper quantitative forecast model first to generate forecasts for a majority of products and then use input from sales, marketing and operations to refine the forecasts. This type would fall under the third category mentioned above which attempts to get the best of both worlds by avoiding two extremes of opinionated forecast decisions and heavy reliance on complex models without understanding them.

Collaborative Forecasting: Real time sharing of demand forecast data among the members of the supply chain is the highlight of this type of forecasting. This method is also called as Collaborative Planning Forecasting and Replenishment (CPFR). This helps in reducing cycle time, improving supply chain efficiency, reducing inventory, increasing service level, reducing safety stock (due to reduced forecast error), and responding quickly to demand changes. An ideal forecasting process in outlined in Figure 3.

Figure 3: Overview of Ideal Forecasting



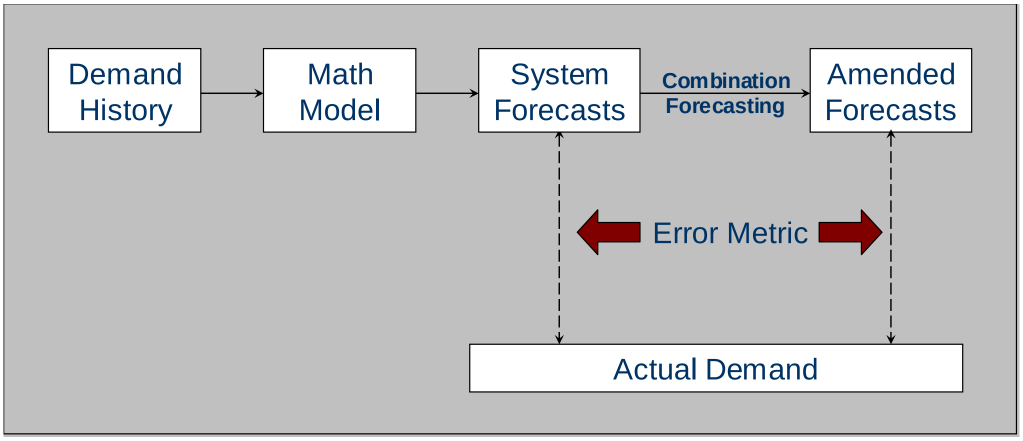
Using a combination of Inventory stratification and forecast accuracy is the best practice for selecting the appropriate forecast method. A key point is that one size does not fit all; likewise the same forecast method does not perform well for all the items in inventory.

<u>Forecast Accuracy</u>

Error metrics play a vital role in comparison of forecast methods.

The accuracy of the system forecast, as well as human overrides, has to be reported at the SKU-level. The key performance metric is the forecast accuracy which can be measured using various accuracy measures.

Figure 4: Forecast Error Metric



Forecast accuracy measures including Mean Absolute Deviation (MAD), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE) are widely used. Of the three, MAD is easily understood and very common.

MAD (units) = Sum of Absolute Forecast Error for #MAD periods / #MAD periods,
where,
Absolute Forecast Error = absolute difference between forecast and demand.
#MAD periods = number of periods considered for calculation (typically, 3).

MAD in units gives the average forecast error in magnitude and is usually applied at a SKU-level. Note that it does not consider direction for which measures like bias and tracking signal have to be used. Typically, 3 periods are used for MAD calculation. To enable comparisons across SKUs, MAD has to be expressed in a common scale like percentage as indicated below. This formulation is similar to MAPE but more lenient.

MAD in % = MAD in units / Average demand for #MAD periods